Exploring the Effectiveness of Hedging in the Indian Commodity Market: A Comparative Analysis of Constant and Dynamic Hedge Ratios Across Agricultural and Non-Agricultural Commodities

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ABSTRACT

This paper delves into the effectiveness of hedging strategies within the Indian commodity market context, encompassing both constant and dynamic optimal hedge ratios. It scrutinizes the performance of hedging across agricultural and non-agricultural commodities, aiming to provide crucial insights into market dynamics for investors and policymakers. Utilizing a sample comprising 13 highly traded commodity futures contracts spanning various commodities such as gold, silver, copper, zinc, aluminium, nickel, lead, cardamom, Mentha oil, cotton, crude palm oil, crude oil, and natural gas, the study investigates hedging effectiveness from 2008 to 2024. Employing Vector Error Correction Model (VECM) and Constant Conditional Correlation Multivariate Generalized Autoregressive Conditional Heteroskedasticity (CCC-MGARCH) models, the paper estimates constant hedge ratios and dynamic hedge ratios, respectively. The study shows that agricultural future contracts provide higher hedging effectiveness (30%) as compared to non-agricultural commodity futures (20%) Understanding the nuances of hedging effectiveness not only aids investors in making informed decisions but also facilitates the development of robust risk management strategies in the Indian commodity market.

Keywords: Hedging effectiveness, Commodity futures, Dynamic hedge ratio

INTRODUCTION

The commodity market stands as a pivotal arena within the financial landscape, fostering trade in both agricultural and non-agricultural commodities. Its roots trace back to ancient civilizations, evolving into a dynamic domain that attracts domestic and international investors alike. Commodity markets serve as a cornerstone of the financial system, offering investors avenues for diversification and risk mitigation. Regulated by the Securities and Exchange Board of India (SEBI), the Indian commodity market operates through esteemed exchanges such as the Multi Commodity Exchange (MCX) and the National Commodity & Derivatives Exchange Limited (NCDEX). This regulatory framework ensures transparency and stability while facilitating various market functions.

The commodity market serves multifaceted purposes, including price discovery, hedging, speculation, portfolio diversification, risk management, and arbitrage opportunities. However, it is not impervious to volatility and fluctuations, stemming from economic indicators, geopolitical events, investor sentiment, and external factors such as natural disasters or pandemics. Moreover, algorithmic and high-frequency trading intensify market volatility, amplifying minor price movements. To mitigate risks inherent in the commodity market, investors often resort to hedging strategies employing derivative instruments like futures and options. Hedging in the futures market entails leveraging futures contracts alongside other obligations, aiming to capitalize on favourable changes in relative spot and futures prices. The primary objective of hedging through futures is to offset potential gains or losses in the spot market with corresponding outcomes in the futures market.

The efficacy of hedging through commodity market futures is a subject of significant scholarly interest. This study delves into the hedging effectiveness within the Indian commodity market context, particularly concerning derivative instruments. It embarks on a two-fold exploration, initially examining both constant and dynamic optimal hedge ratios. Subsequently, the study scrutinizes the hedging effectiveness across agricultural and non-agricultural commodities, seeking to discern potential disparities in performance. Understanding the nuances of hedging effectiveness in commodity market futures not only provides insights into market dynamics but also furnishes valuable knowledge for investors and policymakers alike. By elucidating optimal hedging strategies and evaluating their efficacy, this research contributes to the ongoing discourse surrounding risk management in commodity markets.

LITERATURE REVIEW

Research on the optimal hedge ratio and hedge effectiveness of futures contracts in the Indian commodity market has been a continuous endeavor, with several studies shedding light on this critical aspect. Brajesh Kumar (2009) conducted a study comparing the hedging effectiveness of Indian commodity futures markets with international markets for industrial metals and energy commodities. The findings suggested that Indian commodity futures markets exhibit higher hedging effectiveness, ranging from 30% to 70%, compared to industrial metals and energy commodities, where hedging effectiveness was less than 20%. Whether using constant or dynamic hedge ratios, the results remained consistent, indicating potentially stronger linkages between Indian commodity futures markets and international markets for these commodities.

Similarly, R. Sugirtha (2021) delved into the pricing behavior of Indian commodities markets and evaluated the hedging effectiveness of futures contracts for selected sample commodities traded at the Multi Commodity Exchange India Limited. The study revealed that future prices of commodities significantly determine spot prices, with natural gas futures contracts demonstrating higher hedging effectiveness compared to other sample commodities. This underscores the importance of futures contracts as effective risk management tools in the Indian commodities market.

Dr P Sri Ram (2017) studies the links and co-integrated movement in commodity prices as well as their effects on hedge ratio and hedging effectiveness. The results show a substantial cointegration between spot and future price movement suggesting a long run synchronous changes in the price. Additionally, it has been discovered that the Indian commodity derivatives market facilitates effective hedging opportunities thereby mitigating risk. Along with this a long-term equilibrium relationship between future and spot prices identified in this paper stating there is a unidirectional causality between several commodities in the near term.

Brajesh Kumar, Priyanka Singh and Ajay Pandey (2008) studied hedging effectiveness of futures contract on a financial asset and commodities in Indian market. The study says in an emerging market like India,

the growth of capital and commodity market would depend on the effectiveness of derivatives in mitigating risk. It also states understanding the ideal hedge ratio is essential for risk management because it is essential for formulating a successful hedging plan. The result shows that futures and spot prices are found to be co-integrated in the long run.
In the context of an emerging market like India, the growth of both capital and commodity futures markets relies heavily on the effectiveness of derivatives in managing risk. To this end, understanding the optimal hedge ratio is crucial for devising effective hedging strategies. In a study examining S&P CNX Nifty index futures, gold futures, and soybean futures, various models including OLS, VAR, VECM, and VAR-MGARCH were employed to estimate constant and dynamic hedge ratios. The findings highlighted that VAR-MGARCH model estimates of time-varying hedge ratios provided the highest variance reduction, indicating their efficacy in reducing portfolio risk compared to hedges based on constant hedge ratios. These insights contribute to a deeper understanding of risk management practices in the Indian commodity market and underscore the importance of dynamic hedging strategies in mitigating risk exposure effectively.

DATA

The exploration of hedging effectiveness in the Indian commodity market presents a comparative analysis focusing on both constant and dynamic hedge ratios. This study extends its examination to agricultural commodity Mentha oil and non-agricultural commodities including Aluminium and Natural gas, spanning the period from 2012 to 2024. The data utilized for futures contracts and spot prices originates from the Multi Commodity Exchange of India Ltd (MCX), a prominent commodity exchange established in 2003 by the Government of India. Despite the initial inclusion of gold in the study, its subsequent elimination arose due to observed Arch effect, leading to a refined focus on Mentha oil, Aluminium, and Natural gas. With 3128 observations each for commodity futures contracts and spot prices, this study provides a robust dataset for comprehensive analysis. By examining both agricultural and non-agricultural commodities, it seeks to discern any divergent hedging behaviors and outcomes across these sectors. Additionally, the comparative analysis between constant and dynamic hedge ratios offers valuable insights into the efficacy of different hedging strategies over the studied period.

Table 1: Details of commodity, data period and source

Commodities		Data Periods	Futures Market	Reference spot market for settlement
Metals	Aluminium	01/01/2012 to 18/03/2024	MCX	Mumbai
Energy	Natural Gas	01/01/2012 to 18/03/2024	MCX	Hazira
Agricultural	Mentha oil	01/01/2012 to 18/03/2024	MCX	Chandausi

METHODOLOGY

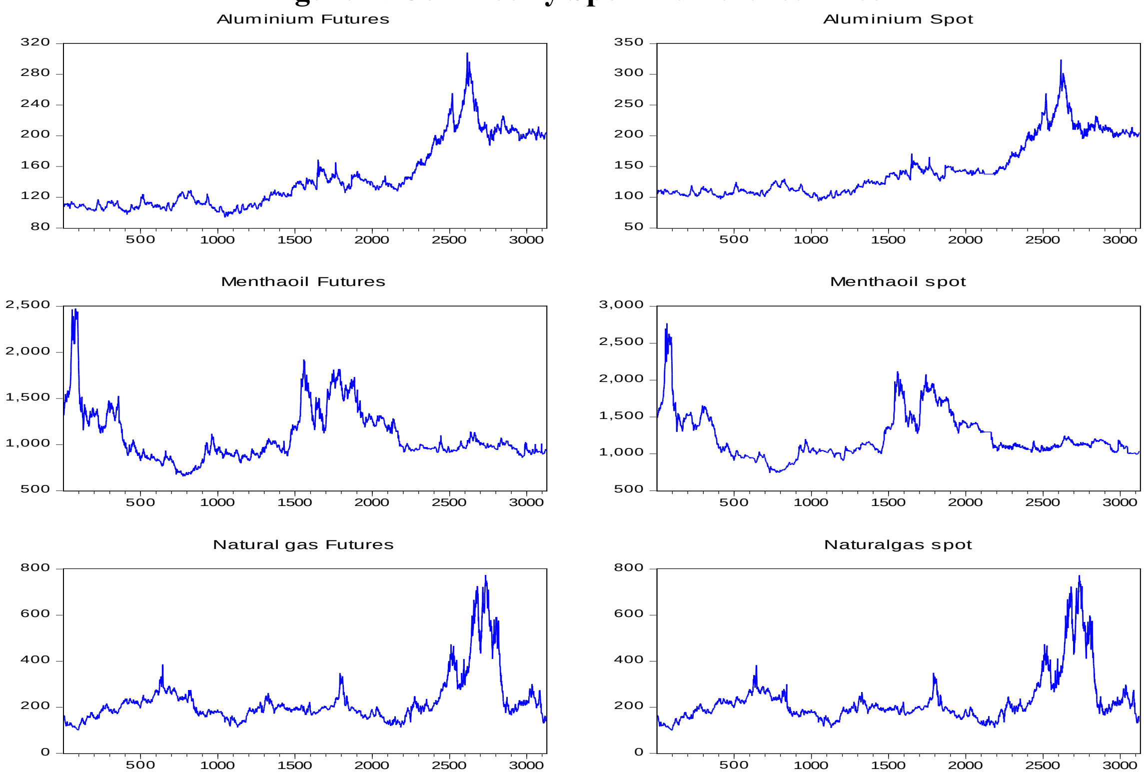
Descriptive statistics serve as foundational tools in research, offering insights into the basic characteristics and distributional properties of data. Measures such as the mean, median, and standard deviation provide a concise summary of the central tendency, variability, and shape of the dataset, respectively. The mean,

calculated as the sum of all observations divided by the total number of observations, offers a representative average value. In contrast, the median represents the middlemost observation when data are arranged in ascending or descending order, offering robustness to outliers. Meanwhile, the standard deviation quantifies the dispersion of values around the mean, providing a measure of data spread. These descriptive statistics collectively facilitate a comprehensive understanding of the dataset's structure and properties, laying the groundwork for subsequent analyses and interpretations.
Additionally, statistical tests such as the Jarque-Bera test are employed to assess the normality of data distributions. By examining skewness and kurtosis, this test evaluates the degree to which the data conforms to a normal distribution. Stationarity tests, including the Augmented Dickey-Fuller test and Phillips-Perron test, ascertain whether a given time series exhibits stationary behavior, essential for reliable modeling and analysis. Furthermore, cointegration tests, such as Johansen's test, investigate long-term relationships between multiple time series, informing on potential co-movements and dependencies. Finally, models such as the Vector Error Correction Model (VECM) and Diagonal BEKK Model are utilized to estimate constant and dynamic hedge ratios, respectively, essential for risk management and hedging strategies. By leveraging these statistical methodologies, researchers gain valuable insights into the characteristics, distributions, and interrelationships within the dataset, enabling informed decision-making and robust analysis in various research domains.

ANALYSIS AND INTERPRETATION

The analysis conducted in this study delves into the hedging effectiveness of the commodity market, focusing on four key commodities: Aluminium, Gold, Natural gas, and Mentha oil. A notable aspect of this investigation is the inclusion of both agricultural and non-agricultural commodities, recognizing their differing levels of tradability within the market. The study spans a significant period from 2012 to 2024, enabling a comprehensive examination of price dynamics and hedging strategies over time.

Figure 1: Commodity Spot and Futures Price



Upon reviewing the price charts depicting futures contract and spot prices for the study period, several notable trends and patterns emerge. These visual representations offer insights into the behavior of commodity prices over time, shedding light on their volatility, seasonality, and overall market dynamics. By juxtaposing futures and spot prices, the charts provide a comparative view of market movements, highlighting instances of convergence or divergence between the two.

DESCRIPTIVE STATISTICS

Descriptive statistics serve as a cornerstone in research, offering researchers a comprehensive understanding of their data's characteristics. Through measures like the mean, median, and standard deviation, researchers can gain valuable insights into the central tendency, variability, and distribution of their data. The mean, or average, provides a concise summary of the data's central value, giving researchers a sense of the typical value in the dataset. Meanwhile, the median offers an alternative measure of central tendency that is less affected by outliers, making it particularly useful for skewed distributions. Together, these measures paint a clear picture of the data's central tendency, allowing researchers to discern patterns and trends within their dataset.

Furthermore, the standard deviation offers critical insights into the spread or dispersion of data points around the mean. By quantifying the extent of variability within the dataset, researchers can gauge the consistency or volatility of their data. A larger standard deviation indicates greater variability, suggesting that data points are more spread out from the mean. Conversely, a smaller standard deviation implies that data points are closer to the mean, indicating greater consistency. Overall, descriptive statistics provide researchers with essential tools to explore, summarize, and interpret their data, laying the groundwork for further analysis and inference.

$$s = \sqrt{\sum_{i=1}^{n} (x_i - \bar{x})}$$

A normality test is crucial in statistical analysis to assess whether the data conforms to a normal distribution, which is characterized by a symmetrical bell-shaped curve. The Jarque-Bera test is a widely used statistical test for normality that evaluates whether a dataset follows a normal distribution based on its skewness and kurtosis. Skewness measures the degree of asymmetry in the distribution, with a normal distribution having a skewness of zero. Positive skewness indicates a longer right tail, while negative skewness indicates a longer left tail. Kurtosis, on the other hand, measures the peakiness or flatness of the distribution. A normal distribution has a kurtosis of three, with values higher than three indicating a peaked distribution and values lower than three indicating a flatter distribution.

Skewness is a measure of the asymmetry of the distribution where a normal distribution has a skewness of zero.

$$s = \frac{\frac{1}{n}\sum_{i=1}^{n} (X_i - \bar{x})^3}{s^3}$$

Kurtosis measures the peakiness of the distribution and a normal distribution has kurtosis of three.

$$k = \frac{\frac{1}{n}\sum_{i=1}^{n} (x_i - \bar{x})^4}{s^4}$$

Descriptive Statistics

Table 2: Descriptive Statics of futures and spot returns

	Variables	Mean	Median	SD	Skewness	Kurtosis	Jarque - Bera	Probability
Aluminium	Futures	144.76	131.63	43.11	1.06	3.17	592.81	0.000
	Spot	146.13	133.90	45.43	1.07	3.19	598.36	0.000
Natural gas	Futures	226.61	196.80	107.01	2.55	10.13	10012.09	0.000
	Spot	226.03	196.40	106.85	2.55	10.14	10031.58	0.000
Mentha oil	Futures	1094.41	983.55	293.28	1.58	6.23	2657.85	0.000
	Spot	1227.87	1116.95	312.55	1.51	5.91	2288.56	0.000

Source: Computation of author

The Jarque-Bera test statistic (JB) is calculated using the skewness and kurtosis of the dataset, comparing them to their expected values under a normal distribution. The formula for the Jarque-Bera test statistic involves the sample skewness (s) and kurtosis (k), along with the sample size (n). The test statistic follows a chi-square distribution, and if its value exceeds a critical threshold, the null hypothesis of normality is rejected, indicating that the data does not follow a normal distribution. Conversely, if the test statistic does not exceed the critical threshold, the null hypothesis cannot be rejected, suggesting that the data may follow a normal distribution.

$$\text{JB} = \frac{n}{6}\left(s^2 + \frac{(k-3)^2}{4}\right)$$

UNIT ROOT TEST (Stationarity Test)

Ensuring data stationarity is crucial in time series analysis to obtain reliable and meaningful results. Stationarity implies that the statistical properties of a time series, such as mean, variance, and autocorrelation, remain constant over time. Non-stationary data, on the other hand, exhibit trends, cycles, or other systematic patterns that can distort statistical analysis and model estimation. Unit root tests like the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are commonly used to assess stationarity by determining the presence of a unit root in the data. If a unit root exists, the series is non-stationary, indicating the need for further transformations or differencing to achieve stationarity.

Table 3: Augmented Dickey-Fuller test statistic

	Level		First Difference	
	I	T & I	I	T &I
Aluminium Future	0.9201	0.5789	0.000	0.001
Aluminium Spot price	0.7717	0.2211	0.000	0.000
Natural gas Futures	0.3023	0.7804	0.001	0.000
Natural gas Spot price	0.1138	0.3498	0.000	0.000
Mentha oil Futures	0.3068	0.644	0.000	0.000
Mentha oil Spot price	0.2961	0.6143	0.0001	0.000

Table 4: Phillips-Perron test statistic

	Level		First Difference	
	I	T & I	I	T &I

Aluminium Future	0.0097	0.0000	0.0001	0.0001
Aluminium Spot price	0.7615	0.2027	0.0001	0.0000
Natural gas Futures	0.1710	0.0000	0.0001	0.0001
Natural gas Spot price	0.0910	0.3365	0.0001	0.0000
Mentha oil Futures	0.0152	0.0000	0.0001	0.0001
Mentha oil Spot price	0.1724	0.4344	0.0001	0.0000

In the context of the ADF and PP tests, conducting them at different levels, including the level and first difference, allows researchers to explore the stationarity of the data under various conditions. Testing at the level examines the original series, while testing at the first difference evaluates the changes between consecutive observations. By incorporating intercepts and trends into the tests, analysts can account for potential systematic components in the data. Ultimately, the interpretation of test results hinges on the significance level (typically set at 0.05), where p-values below this threshold indicate rejection of the null hypothesis of a unit root, implying stationarity. Conversely, p-values above the threshold suggest failure to reject the null hypothesis, indicating non-stationarity. Careful consideration of these test outcomes informs subsequent modelling decisions, ensuring that time series analyses are conducted on stationary data, thus enhancing the reliability and validity of the findings.

COINTEGRATION TEST

Cointegration tests, such as the Johansen test, play a crucial role in assessing the long-term relationship between multiple time series variables. Johansen's test encompasses two main forms: Trace tests and Maximum Eigenvalue tests, each serving different purposes in evaluating cointegration. In Trace tests, the null hypothesis (H0) typically assumes a specific number of cointegrating vectors (K = K0). The test statistic is computed using the maximum likelihood ratio, which involves the summation of logarithms of (1 - λi), where λi represents the eigenvalues derived from the estimation. This statistic aids in assessing the number of linear combinations present in the time series data that exhibit cointegration. The Trace test helps determine whether the number of cointegrating relationships in the data is consistent with the null hypothesis.

On the other hand, Maximum Eigenvalue tests evaluate whether the number of cointegrating relationships exceeds a specified threshold (K = K0 + 1). The test statistic, calculated as -T times the natural logarithm of (1 - λ(γ+1)), involves the largest eigenvalue (λ(γ+1)) among the estimated eigenvalues. This test helps ascertain whether an additional cointegrating relationship exists beyond what is assumed under the null hypothesis. By comparing the test statistic to critical values, researchers can make inferences about the presence and nature of cointegration in the time series data, providing valuable insights into their long-term dynamics and relationships. Trace test statistic is calculated by using maximum likelihood ratio as per the following formula

$$Trace(r,k) = T \sum_{i=\Gamma+1}^{k} ln(1-\lambda_i)$$

Maximum Eigenvalue test defined as a non-zero vector which, when a linear transformation is applied to it, changes by a scalar factor. H_0: K = K_0, H_0: K = $K_0 + 1$

Maximum eigenvalue test is calculated by the following formula

$$\lambda_{\max}(r, r+1) = -T \ln\left(1-\lambda_{\gamma+1}\right)$$

Table 5: Johansen Cointegration Test

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.198793	907.1064	95.75366	0.0001
At most 1 *	0.037623	224.9110	69.81889	0.0000
At most 2 *	0.028890	106.8721	47.85613	0.0000
At most 3	0.003381	16.63936	29.79707	0.6665
At most 4	0.001653	6.214130	15.49471	0.6702
At most 5	0.000364	1.121360	3.841466	0.2896

Trace test indicates 3 cointegrating eqn(s) at the 0.05 level
* Denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.198793	682.1954	40.07757	0.0001
At most 1 *	0.037623	118.0389	33.87687	0.0000
At most 2 *	0.028890	90.23271	27.58434	0.0000
At most 3	0.003381	10.42523	21.13162	0.7041
At most 4	0.001653	5.092770	14.26460	0.7301
At most 5	0.000364	1.121360	3.841466	0.2896

Max-eigenvalue test indicates 3 cointegrating eqn(s) at the 0.05 level
* Denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

The results of the unrestricted cointegration rank tests shown in table 5, both the Trace test and the Maximum Eigenvalue test, suggest that there are 3 cointegrating equations at the 0.05 significance level. This means that there is evidence of long-term relationships among the variables being analyzed. In both tests, the null hypothesis is rejected at the 0.05 level for the cases of "None" (indicating no cointegration) and "At most 1" (indicating up to 1 cointegrating equation). However, for the cases of "At most 2" and beyond, the null hypothesis cannot be rejected, suggesting that there are at least 3 cointegrating equations present in the data.

Therefore, based on these results, it can be inferred that there are 3 cointegrating relationships among the variables under investigation. This implies that these variables move together in the long run, exhibiting a stable equilibrium relationship despite short-term fluctuations.

Autoregressive Conditional Heteroskedasticity (ARCH) Effect

The ARCH effect, or Autoregressive Conditional Heteroskedasticity, refers to the phenomenon where the volatility of a time series is not constant over time but instead exhibits clustering. This means that periods of low volatility tend to be followed by periods of high volatility, and vice versa. To detect volatility clustering, researchers often employ the ARCH LM (Lagrange Multiplier) test. If the series passes the ARCH LM test, indicating the presence of autocorrelation in the squared residuals, it suggests that the data exhibits ARCH effects. In such cases, ARCH models, such as the Diagonal BEKK ARCH model, can be applied to analyze and model the time-varying volatility more effectively. The qualification for the ARCH LM test typically involves checking the p-value, with a threshold usually set at less than 0.05 for statistical significance. If the p-value is below this threshold, it suggests that the series exhibits significant autocorrelation in squared residuals, indicating the presence of ARCH effects.

Table 5: Results of ARCH LM Test

	t statistic	**p value**
Aluminium Futures	52.14	0.00
Aluminium Spot	39.13	0.00
Natural gas Futures	45.57	0.00
Natural gas Spot	282.86	0.00
Mentha oil Futures	44.49	0.00
Mentha oil Spot	115.15	0.00

The results of the Arch LM Test indicate significant evidence of volatility clustering in all the commodity futures and spot markets examined. The Arch LM Test statistic values for Aluminium Futures, Aluminium Spot, Natural Gas Futures, Natural Gas Spot, Mentha Oil Futures, and Mentha Oil Spot are all substantially high, indicating strong evidence of autocorrelation in the squared residuals of the time series data. Furthermore, the p-values associated with each statistic are reported as 0.00, which is less than the conventional significance level of 0.05. This indicates that the null hypothesis, which states that there is no volatility clustering (i.e., no ARCH effect), is strongly rejected in all cases.

Therefore, based on these results, it can be concluded that the time series data for Aluminium Futures, Aluminium Spot, Natural Gas Futures, Natural Gas Spot, Mentha Oil Futures, and Mentha Oil Spot exhibit significant volatility clustering. This suggests that periods of high volatility tend to be followed by subsequent periods of similarly high volatility, and vice versa, indicating a non-constant variance structure over time. Consequently, employing ARCH-type models, such as the Diagonal BEKK ARCH Model, may be appropriate for capturing and modeling the dynamic volatility behavior present in these markets.

VECM (Vector Error Correction Model)

Choosing the Vector Error Correction Model (VECM) for estimating the constant hedge ratio is a prudent decision when there is evidence of cointegration between spot and futures prices. Cointegration implies a long-term relationship between these prices, indicating that they move together over time despite short-term fluctuations. By employing the VECM, which accounts for both short-term dynamics and long-term equilibrium adjustments, investors can obtain accurate estimates of the constant hedge ratio. The VECM model captures the dynamic adjustments between spot and futures prices, allowing for the estimation of a stable constant hedge ratio that reflects the underlying relationship between these prices. This constant hedge ratio serves as a crucial parameter in hedging strategies, enabling investors to mitigate price risks effectively and optimize their portfolio performance.

Furthermore, by utilizing the VECM, investors can gain insights into the speed of adjustment towards the long-term equilibrium relationship between spot and futures prices. This information is valuable for implementing timely hedging decisions and managing risks in volatile financial markets. Overall, the VECM offers a robust framework for estimating the constant hedge ratio and enhancing risk management practices in the context of spot and futures price relationships.

The hedge ratio formula you provided calculates the ratio between the covariance of futures and spot prices and the variance of futures prices. This ratio represents the relationship between changes in spot prices and changes in futures prices, serving as a measure of how effectively futures contracts can be used to hedge against spot price movements.

$$Hedge\ Ratio\ = \frac{Covariance\ of\ future\ and\ spot}{Variance\ of\ future}$$

On the other hand, hedge effectiveness, represented by the variable (E), is calculated as the difference between the variance of the unhedged portfolio ((Var(u))) and the variance of the hedged portfolio ((Var(H))), divided by the variance of the unhedged portfolio. This formula quantifies the reduction in portfolio risk achieved through hedging, with a higher value indicating greater effectiveness in mitigating risk through hedging strategies.

Hedge effectiveness can be calculated by

$$\text{Hedging Effectiveness} = \frac{Var(u) - Var(H)}{Var(u)}$$

Together, these formulas provide essential metrics for evaluating the efficacy of hedging strategies in managing price risk. By calculating the hedge ratio and hedge effectiveness, investors can assess the potential impact of futures contracts on portfolio volatility and make informed decisions to optimize risk-adjusted returns.

Table 6: Constant hedge ratio and Hedging Effectiveness estimated using VECM Model

	Hedge Ratio	Hedge Effectiveness
Aluminium	0.635455	37.71
Natural gas	0.76998	2.22
Mentha oil	0.048383	1.772

For aluminium, the hedge ratio is 0.635455, indicating a moderate level of hedging against spot price movements. Additionally, the hedge effectiveness is 37.71%, suggesting a significant reduction in portfolio risk through hedging. In the case of natural gas, the hedge ratio is higher at 0.76998, indicating a stronger relationship between futures and spot prices. However, the hedge effectiveness is relatively low at 2.22%, implying a limited reduction in portfolio risk through hedging compared to aluminium. Mentha oil exhibits the lowest hedge ratio among the commodities listed, indicating a weaker relationship between futures and spot prices. Despite this, the hedge effectiveness is 1.772%, suggesting a modest reduction in portfolio risk through hedging.

The observation that non-agricultural commodities have higher hedging effectiveness compared to agricultural commodities aligns with expectations, as non-agricultural commodities often exhibit more predictable price movements and stronger correlations between futures and spot prices. This insight underscores the importance of considering the specific characteristics of each commodity market when implementing hedging strategies to effectively manage price risk.

Diagonal BEKK GARCH Model

The Diagonal BEKK GARCH model is utilized to estimate the dynamic hedge ratio and hedging effectiveness, particularly in the context of financial markets where volatility clustering and time-varying covariance are prevalent. The model explicitly captures the dynamics of conditional covariance, allowing for a more accurate assessment of risk and the effectiveness of hedging strategies.

The equation for the Diagonal BEKK GARCH model is represented as:

$$H_{t = \Omega + \alpha_1 e_t - 1 e'_{t-1} + \beta_1 H_{t-1}}$$

In this equation:

- (H_t) represents the conditional covariance matrix at time (t).
- (Ω) denotes the constant covariance matrix.
- (e_{t-1}) is the vector of squared residuals at time (t-1).
- (α_1) captures the impact of past squared innovations on conditional covariance.
- (β_1) represents the impact of past conditional covariance matrices on the current conditional covariance.

By incorporating these components, the Diagonal BEKK GARCH model provides a dynamic framework to estimate the time-varying conditional covariance, considering the autocorrelation and dynamics of volatility clustering present in the data. This model is particularly useful in financial markets where volatility patterns change over time, allowing for more accurate risk assessment and hedging strategies.

Time Varying Hedge ratio

The hedge ratio is estimated using the covariance between the futures and spot prices, divided by the variance of the futures price. This ratio provides insight into the relationship between the two prices and is essential for determining an effective hedging strategy.

The formula to estimate the hedge ratio is:

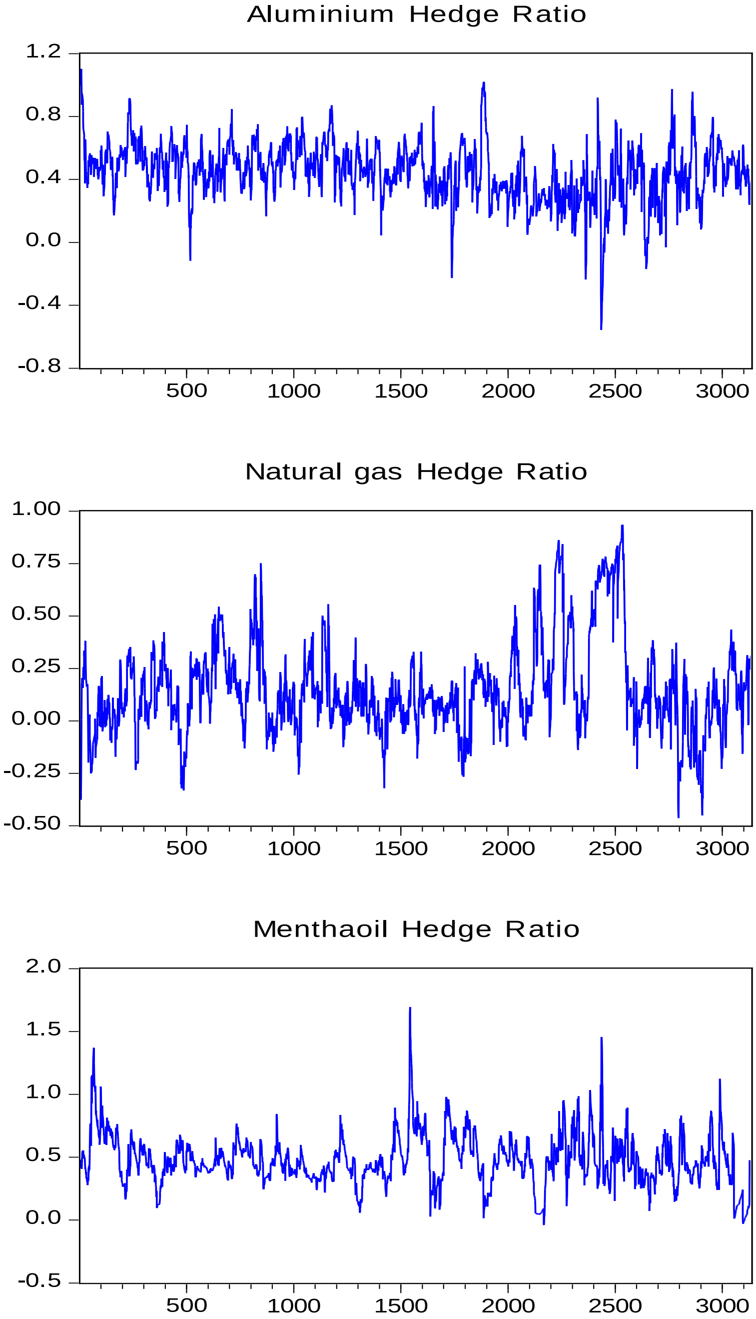
$$Hedge\ Ratio\ = \frac{Covariance\ of\ future\ and\ spot}{Variance\ of\ future}$$

Once the hedge ratio is calculated, it indicates how many units of the spot market need to be hedged using one unit of the futures contract to effectively mitigate risk. A higher hedge ratio suggests a stronger relationship between the futures and spot prices, indicating a more effective hedging strategy.

The time-varying hedge ratio is presented in the Figure No 2 is around the naive hedge ratio of 1:1, it suggests that the futures and spot prices have a strong and stable relationship over time. A hedge ratio of 1 indicates a perfect correlation between the changes in the futures and spot prices, implying that one unit of the spot market can be hedged using exactly one unit of the futures contract. This scenario is ideal for hedging purposes because it implies that the futures contract effectively tracks the movements in the spot market. It allows investors or traders to hedge their positions in the spot market by taking offsetting positions in the futures market, thereby mitigating their risk exposure. A stable and close-to-unity hedge ratio simplifies the hedging process and reduces the need for frequent adjustments to the hedge ratio. It provides confidence to market participants that their hedging strategies will effectively protect them against adverse price movements in the spot market.

Overall, a time-varying hedge ratio around 1:1 indicates a strong and reliable relationship between the futures and spot prices, facilitating efficient risk management and hedging in the financial markets.

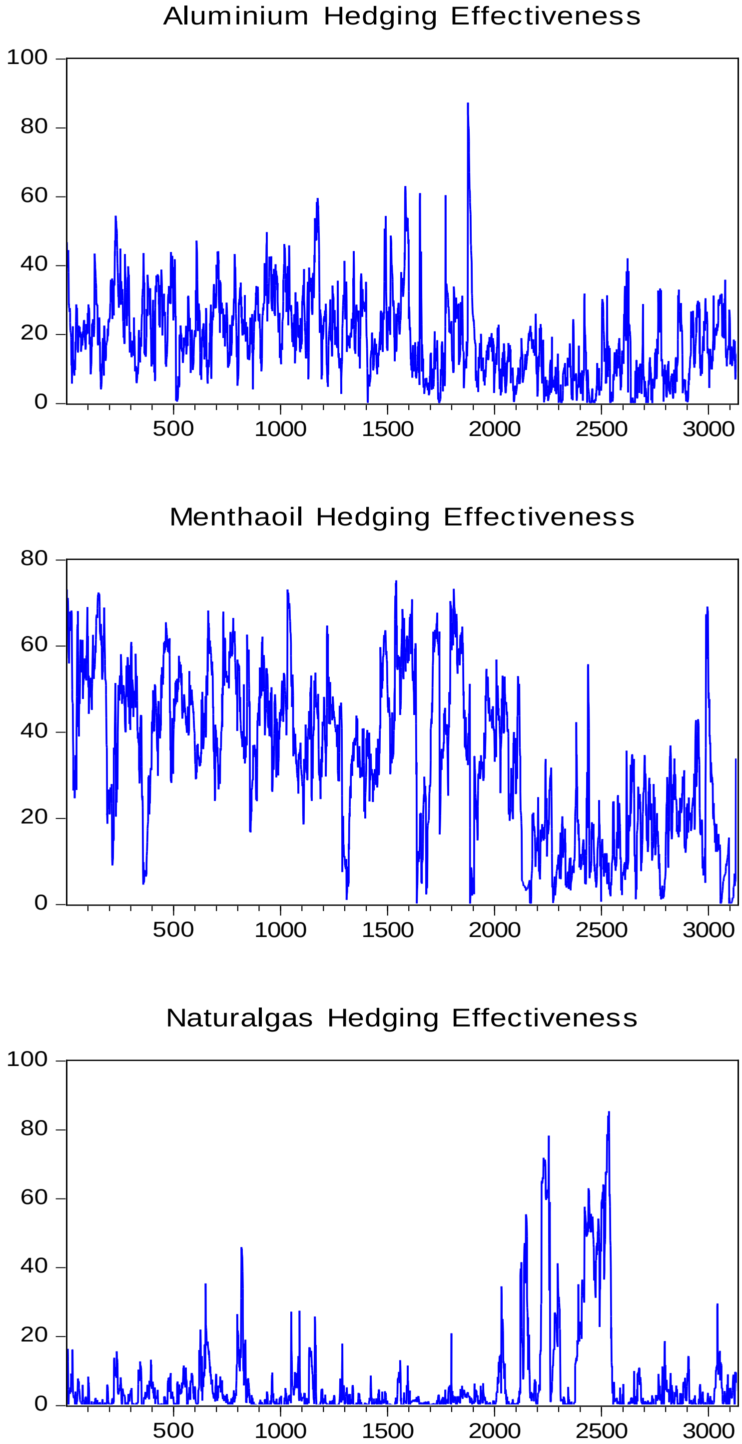
Figure 2: Hedge Ratio



Time varying Hedging Effectiveness

The observation that Mentha oil exhibits higher hedging effectiveness compared to non-agricultural commodities such as aluminium and natural gas highlights an interesting trend in the commodities market. With an average hedging effectiveness of 33%, Mentha oil proves to be a more reliable instrument for hedging against price fluctuations compared to aluminium and natural gas, which have average hedging effectiveness rates of 18% and 6% respectively.

Figure 3: Hedging Effectiveness of Commodities



This discrepancy in hedging effectiveness could be attributed to various factors specific to each commodity. Mentha oil, being an agricultural commodity, may be subject to more predictable supply and demand dynamics or may be influenced by factors that are more easily hedged against using futures contracts. On the other hand, non-agricultural commodities like aluminium and natural gas may face greater volatility due to factors such as geopolitical tensions, global economic conditions, or changes in industrial demand, making them more challenging to hedge effectively.

CONCLUSION

This study provides valuable insights into the hedge ratio and hedging effectiveness of both agricultural and non-agricultural commodities, shedding light on the comparative advantages and limitations of utilizing futures markets for risk management purposes. By employing both Vector Error Correction Model (VECM) and Diagonal BEKK model, we have examined the dynamics of hedging in the context of volatile commodity markets.

The findings reveal a notable discrepancy in hedging effectiveness between agricultural and non-agricultural commodities. Agricultural commodities, represented here by Mentha oil, demonstrate a consistently higher hedging effectiveness, with an average above 30%. On the contrary, non-agricultural commodities such as aluminium and natural gas exhibit significantly lower hedging effectiveness, averaging below 20%. This discrepancy underscores the importance of considering the unique characteristics and market dynamics of different commodities when formulating hedging strategies.

Further analysis using the VECM model and Diagonal BEKK model elucidates the role of constant and dynamic hedge ratios in risk management. The VECM model allows for the estimation of constant hedge ratios, particularly useful when futures and spot prices are cointegrated. In contrast, the Diagonal BEKK model enables the calculation of dynamic hedge ratios, providing insights into the time-varying nature of hedging effectiveness.

The observed disparity in hedging effectiveness between agricultural and non-agricultural commodities suggests distinct market behaviors and risk profiles. Agricultural commodities may benefit from more predictable supply and demand dynamics, making them conducive to effective hedging strategies. Conversely, non-agricultural commodities are subject to a broader range of factors, including geopolitical events, economic conditions, and industrial demand fluctuations, posing challenges for effective risk mitigation through futures markets.

These findings have significant implications for market participants and investors. Hedgers operating in agricultural commodity markets may find futures markets to be reliable tools for managing price volatility and mitigating risk. Conversely, hedgers dealing with non-agricultural commodities may need to explore alternative risk management strategies or exercise caution when relying solely on futures markets for hedging purposes.

In conclusion, this study underscores the importance of tailored risk management approaches tailored to the specific characteristics of different commodity markets. Understanding the nuances of hedging effectiveness across agricultural and non-agricultural commodities can empower market participants to make informed decisions and optimize risk-adjusted returns in the dynamic landscape of commodity markets. Further research exploring the determinants of hedging effectiveness and the impact of market conditions on risk management strategies would contribute to a deeper understanding of commodity market dynamics and enhance risk management practices in the future.

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